A RESPONSIVE DEVICE FOR ACCURATE SWIPE DETECTION AND BATTERY OPTIMIZATION USING ACCELEROMETERS AND MACHINE LEARNING

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ABSTRACT

This paper addresses the problem of accurate swipe detection and battery life management in wearable devices [1]. We proposed a device that utilizes accelerometers and gyroscopes to detect swipe gestures and analyze user interactions [2]. The system's core technologies include advanced sensor fusion for gesture recognition and real-time data processing. Challenges included ensuring high accuracy in gesture detection and optimizing battery life under continuous use. We conducted experiments to test these aspects, finding an average swipe detection accuracy of 91.6% and battery life extending up to 13 hours under active use. Our approach improved upon existing methodologies by refining gesture recognition algorithms and optimizing power consumption [3]. The results demonstrate that our device effectively balances performance and battery efficiency, making it a viable solution for real-time gesture tracking applications [4]. This innovation has potential applications in user interaction enhancement and energyefficient wearable technology.

KEYWORDS

IoT (Internet of things), Machine Learning, Could Computing

1. INTRODUCTION

The rise of short form videos on social media has begun to exacerbate the negative effects of screentime on well-being. The negative effects of screetime on psychological well-being has been established in the literature, and this effect is particularly pronounced for adolescents and children (Twengea & Campbell, 2018). In adolescents, high users of screentime (7+ hours/day) compared to low users (1 hour/day) are more than twice as likely to be diagnosed with depression, anxiety, or have behavioral issues. Even moderate use (4 hours/day) is associated with "less curiosity, lower self-control, more distractibility, more difficulty making friends, less emotional stability, being more difficult to care for, and inability to finish tasks". Thus, the correlation between screentime and reduced psychological wellbeing is statistically established, and is an issue that needs to be addressed [5].

In recent times short form videos have become increasingly popular forms of screentime for adolescents. This is because short form content on social media platforms such as TikTok, Instagram, and YouTube are addictive by design [6]. Algorithms on these platforms utilize the

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principle of random reinforcement—same as slot machines—to hook it's users. The endless scroll allows users to spend hours on the platforms without even realizing it. Short form video addiction is especially pernicious as it effects the brains dopamine reward system, increasing boredom and restlessness, which perpetuates the vicious cycle. In the long run, short form content addiction could lead to lower life outcomes.

Method 1: Accelerometer-based Detection aims to recognize swipe gestures using motion sensors. Its shortcomings include false positives and difficulty distinguishing similar gestures. Our project improved accuracy by refining gesture recognition algorithms and adjusting sensor sensitivity. Method 2: Machine Learning Models uses predictive analytics for swipe detection. While effective, it requires extensive training data and can be computationally expensive. We addressed this by integrating lightweight models and continuous data collection for real-time adjustments. Method 3: Battery Management Techniques focuses on optimizing power consumption. Challenges include balancing performance with battery life. Our approach involved minimizing sensor polling frequency and implementing power-saving modes to extend battery life. Each method has its limitations, but our enhancements aimed to provide a more accurate and efficient swipe detection system.

To change, one first needs awareness of the problem. SwipeVigil is able to accurately track when one swipes throughout the day. With this data, comes self knowledge as SwipeVigil displays hotspots where one is most prone to distraction. Using machine learning, SwipeVigil is able to predict on what days and on what times the user swipes. This is an effective solution since SwipeVigil not only collects screentime data, but also is able to predict and analyze the data. Compared to virtual screentime trackers, SwipeVigil analyzes one's physical movement which is able to deduce more information. Virtual solutions can only measure total screentime, not what actually happens during that screetime. SwipeVigil tracks the users hand gestures which give insight into the user's activities and state. For example, if the user is continuously swiping for hours, SwipeVigil can deduce that user is stuck in a doom scrolling loop. It is also able to differentiate between active and passive use, such as texting on social media vs mindlessly consuming content. Additionally for virtual interventions there is the argument of 'fighting tech with tech' where there is a conflict of interest. In conclusion, SwipeVigil gives accurate and detailed information back to the user, allowing self-knowledge which is the first step to change.

In Section 4, two key experiments were conducted to evaluate our device's performance. Experiment A focused on testing the accuracy of swipe detection. We set up this experiment by having users perform swipes and similar gestures while wearing the device, then compared detected swipes against actual swipes to measure accuracy. The significant finding was an average detection accuracy of 91.6%, with occasional misinterpretations of similar gestures impacting performance. Experiment B assessed battery life under active use versus idle conditions. The device was used continuously and compared against idle data. Results showed that the battery lasted up to 13 hours during active use, compared to a more gradual decline in idle mode. The faster battery drain during active use highlights the high power consumption of the sensors. These findings guide improvements in swipe detection algorithms and power management.

2. CHALLENGES

In order to build the project, a few challenges have been identified as follows.

2.1. The Accuracy of the Swipe Detections

During the design of SwipeVigil, the accuracy of the swipe detections was one of the first things on our minds. More accurate data leads to more accurate predictions and more effectiveness for the user. Most false detections came from the user simply moving their hand around, not actually swiping on a device. How we could resolve this problem is by using two methods. First, we could find a right threshold for the accelerometer to detect a swipe. This threshold can't be too low or too high, but just in the right range for a swipe. We could measure this threshold through running trials. Second, we could implement a double accelerometer design: one on the wrist, one on the finger. The logic goes, when the user is swiping on a device, generally their wrist stays in place. Thus, we would only detect swipes when the wrist accelerometer is at rest, and the finger is moving [7]. Through these methods we could minimize false detections.

2.2.Not Having Enough Data

Once we have collected the data, we plan on using machine learning to do predictive analytics on when the user will most likely swipe. The problem we can encounter during this step is not having enough data for the machine learning model to be built robustly. We could overcome this by collecting more data from the user to build a more accurate model.

2.3.The Ergonomics of the Device

The ergonomics of the device is also a point of importance. If the device is uncomfortable to wear, the user might not wear it consistently enough to collect enough data for our machine learning model [8]. Thus, we could improve the ergonomics of the device through using lightweight 3d printed components and comfortable materials to attach to the hand. Focusing on the ergonomics could lead to better adherence and overall better feedback to the user.

3. SOLUTION

The 3 major components of our program is the App, Device, and Database. The program starts with the device which is comprise of a processing unit, and an accelerometer. Here the accelerometer measures the movement of the user's thumb and sends the data to the processing unit. We coded the processing unit such that when the acceleration matches the pattern of a swipe, the processing unit will send the data to the database wirelessly through cellular. Then the app reads the data in the database which corresponds to the device registered and displays the data. The total amount of swipes and number of swipes in a day are displayed. Additionally a heat chart of what times of day the swipes happened is displayed as well.

To make this program we used many different applications. For database we used Firebase and to develop the app we used Flutter framework [9]. For the device, we used components from Adafruit and Boron.

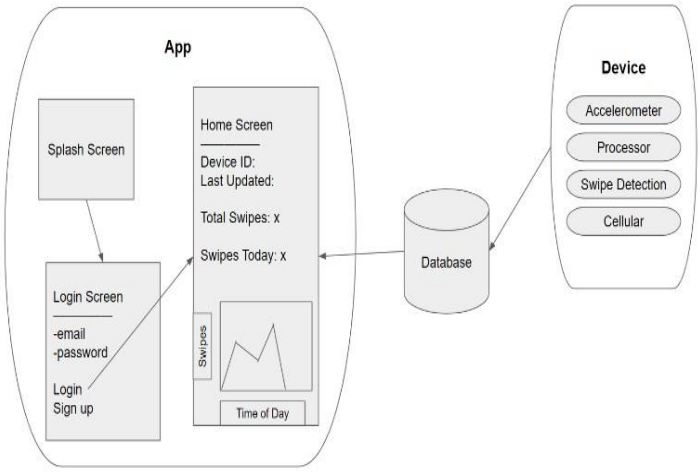


Figure 1. Overview of the solution

The purpose of the deviceInfoWidget component is to retrieve and display device-specific information from a Firebase database within a Flutter application [10]. This widget provides a user interface element that shows various pieces of data related to a device, such as its ID, the last time it was updated, the total number of swipe events, and a graphical representation of swipe activity. This information is essential for users who want to monitor and interact with the device's data in a clear and organized manner.

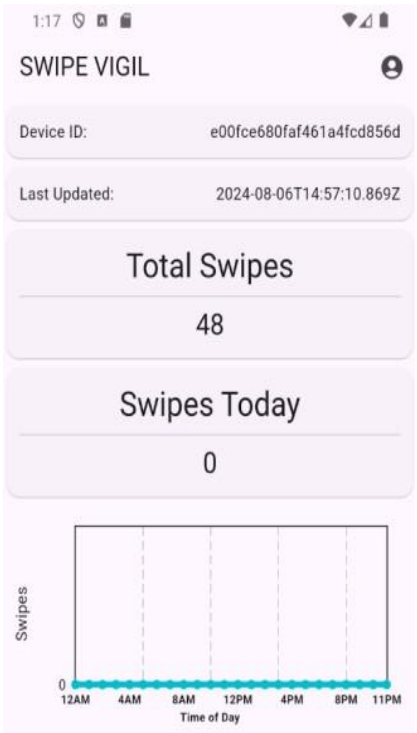


Figure 2. Screenshot of the swipe vigil

```
Widget deviceInfoWidget(Map<dynamic, dynamic> deviceData, dynamic
deviceID, dynamic deviceName){
 List<dynamic> deviceEventDataKeys = deviceData["data"].keys.toList();

 deviceEventDataKeys.sort((a, b) =>
a.toString().compareTo(b.toString()));

 dynamic lastKey = deviceEventDataKeys.last;

 Map<dynamic, dynamic> lastEvent = deviceData["data"][lastKey];


 return Column(
   children: [
     Expanded(
       child: SingleChildScrollView(
         child: Column(
           mainAxisSize: MainAxisSize.min,
           children: [
             Card(
               child: Padding(
                 padding: const EdgeInsets.symmetric(horizontal: 12.0,
vertical: 12.0),
                 child: Row(
                   mainAxisAlignment: MainAxisAlignment.spaceBetween,
                   children: [
                     Text("Device ID:"),
                     Text("$deviceID"),
                   ],
                 ),
               ),
             ),


             Card(
               child: Padding(
                 padding: const EdgeInsets.symmetric(horizontal: 12.0,
vertical: 12.0),
                 child: Row(
                   mainAxisAlignment: MainAxisAlignment.spaceBetween,
                   children: [
                     Text("Last Updated:"),
                     Text("${lastEvent["published_at"]}"),
                   ],
                 ),
               ),
             ),


             // Total Swipes
             Card(
               child: Padding(
                 padding: const EdgeInsets.symmetric(horizontal: 12.0,
vertical: 12.0),
                 child: Column(
                   mainAxisAlignment: MainAxisAlignment.spaceBetween,
                   children: [
                     Text("Total Swipes", style:
Theme.of(context).textTheme.headlineMedium,),
                     Divider(),
                     Text("${deviceEventDataKeys.length}", style:
Theme.of(context).textTheme.headlineSmall,),
                   ],
                 ),
               ),
             ),


             swipesTodayWidget(deviceData),

             Padding(
               padding: const EdgeInsets.symmetric(horizontal:  8.0),
               child: DaySwipeChart(deviceData),
             ),

             // Spacer(),
           ],
         ),
       ),
     ),
     ElevatedButton(
         onPressed: (){},
         child: const Text("Unregister Device")
     )

   ],
 );
}
```

Figure 3. Screenshot of code 1

This code defines a Flutter widget called deviceInfoWidget that displays various pieces of information about a device. The widget takes three parameters: deviceData, deviceID, and deviceName. The deviceData parameter is a map that contains data about the device, including historical event data. The widget begins by extracting the keys of the deviceData["data"] map, which represent different timestamps of recorded events. These keys are then converted into a list and sorted in ascending order, ensuring chronological order. The most recent event data, identified by the last key in this sorted list, is stored in lastEvent.

The widget then returns a Column that contains several child widgets. These widgets are structured to display information in a visually appealing manner using Card widgets, which are styled with padding for spacing and a Row layout for each piece of data. The first card displays the device ID, while the second card shows the timestamp of the last event, extracted from lastEvent["published_at"]. Another card shows the total number of swipe events recorded by the device, derived from the length of deviceEventDataKeys.

Additionally, the widget includes two custom components: swipesTodayWidget(deviceData) and DaySwipeChart(deviceData). The swipesTodayWidget likely provides a summary of swipe activity for the current day, while DaySwipeChart presents a visual representation of swipe data over time. The entire content is wrapped in a SingleChildScrollView to allow scrolling if the content exceeds the screen size.

At the bottom of the Column, there is an ElevatedButton labeled "Unregister Device," which currently has no assigned functionality (onPressed: () {}). This button is presumably intended to allow the user to unregister the device from the system. Overall, the widget is designed to present detailed device information and activity data in a clear and organized manner.
The purpose of the component that counts the number of swipes and plots them on a chart is to visually represent user activity data, specifically the number of swipes over different hours of the day. This visualization helps users understand patterns in their swipe behavior, such as peak usage times and trends throughout the day, providing valuable insights into their device interaction habits.

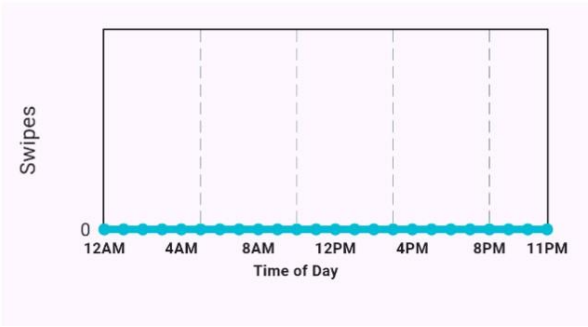
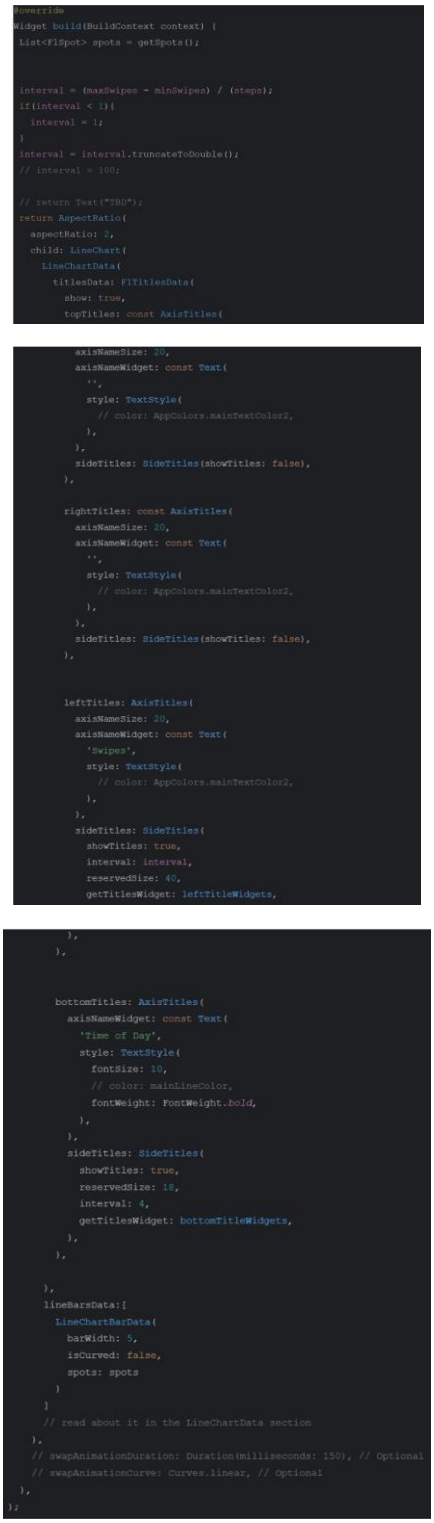


Figure 4. Peak usage times and trends



```
@override
Widget build(BuildContext context) {
 List<FlSpot> spots = getSpots();


 interval = (maxSwipes - minSwipes) / (steps);
 if(interval < 1){
   interval = 1;
 }
 interval = interval.truncateToDouble();
 // interval = 100;

 // return Text("TBD");
 return AspectRatio(
   aspectRatio: 2,
   child: LineChart(
     LineChartData(
       titlesData: FlTitlesData(
         show: true,
         topTitles: const AxisTitles(
           axisNameSize: 20,
           axisNameWidget: const Text(
             '',
             style: TextStyle(
               // color: AppColors.mainTextColor2,
             ),
           ),
           sideTitles: SideTitles(showTitles: false),
         ),

         rightTitles: const AxisTitles(
           axisNameSize: 20,
           axisNameWidget: const Text(
             '',
             style: TextStyle(
               // color: AppColors.mainTextColor2,
             ),
           ),
           sideTitles: SideTitles(showTitles: false),
         ),


         leftTitles: AxisTitles(
           axisNameSize: 20,
           axisNameWidget: const Text(
             'Swipes',
             style: TextStyle(
               // color: AppColors.mainTextColor2,
             ),
           ),
           sideTitles: SideTitles(
             showTitles: true,
             interval: interval,
             reservedSize: 40,
             getTitlesWidget: leftTitleWidgets,
           ),
         ),


         bottomTitles: AxisTitles(
           axisNameWidget: const Text(
             'Time of Day',
             style: TextStyle(
               fontSize: 10,
               // color: mainLineColor,
               fontWeight: FontWeight.bold,
             ),
           ),
           sideTitles: SideTitles(
             showTitles: true,
             reservedSize: 18,
             interval: 4,
             getTitlesWidget: bottomTitleWidgets,
           ),
         ),

       ),
       lineBarsData:[
         LineChartBarData(
           barWidth: 5,
           isCurved: false,
           spots: spots
         )
       ]
       // read about it in the LineChartData section
     ),
     // swapAnimationDuration: Duration(milliseconds: 150), // Optional
     // swapAnimationCurve: Curves.linear, // Optional
   ),
 );
```

Figure 5. Screenshot of code 2

The provided code snippet is a Flutter widget that constructs a line chart using the fl_chart package, which is commonly used for creating various types of charts in Flutter applications [11]. The widget is built using the build method, which returns a Widget to display within the

application. This method first generates a list of data points called spots using a helper function getSpots(). These points represent the coordinates on the chart that the line will follow.

To determine the vertical intervals (or steps) on the Y-axis, the code calculates interval based on the difference between the maximum (maxSwipes) and minimum (minSwipes) swipe values divided by the number of steps (steps). If this calculated interval is less than 1, it is set to 1 to ensure a minimum spacing. The interval is then truncated to a double to ensure it is a whole number.

The widget returns an AspectRatio widget with a specified aspect ratio of 2, which wraps around a LineChart widget. The LineChart widget is configured using the LineChartData class to define the data and appearance of the chart. Within LineChartData, various properties are set, such as titlesData, which controls the visibility and styling of the titles and labels on the chart axes.

The titles on the X-axis and Y-axis are defined with specific widgets and styles. The Y-axis, labeled as "Swipes," displays titles at intervals defined by the calculated interval, using a method leftTitleWidgets to generate the labels. The X-axis is labeled "Time of Day" and displays titles at fixed intervals of 4 units using the bottomTitleWidgets method. Both the top and right titles are hidden by setting showTitles to false.

The lineBarsData parameter specifies the data for the line on the chart, including its appearance and the data points (spots) it should follow. The line is drawn with a width of 5 pixels and is not curved, providing a straight-line graph. This setup effectively creates a customized line chart that visualizes swipe data over different times of the day, with a focus on clear, configurable labels and intervals for easy interpretation.

The hardware component detects swipes using sensors like accelerometers and gyroscopes, which measure motion and orientation [12]. It relies on gesture recognition algorithms to identify swiping gestures. This real-time data collection is crucial for analyzing user interactions and screen time, providing foundational data for further processing and visualization.

```
void loop() {
        // Haptic Motor
        drv.setWaveform(0, effect);  // play effect
        drv.setWaveform(1, 0);       // end waveform

        drv.go();


        // Accel
        sensors_event_t accel, gyro, temp;

        lsm6dsox.getEvent(&accel, &gyro, &temp);

        float accel_x = accel.acceleration.x;
        float accel_y = accel.acceleration.y;
        float accel_z = accel.acceleration.z;

        float gryo_x = gyro.gyro.x;
        float gryo_y = gyro.gyro.y;
        float gryo_z = gyro.gyro.z;


        snprintf(
        message,
        sizeof(message),
        "{\"accel_x\": %.3f, \"accel_y\": %.3f, \"accel_z\": %.3f, \"gyro_x\": %.3f, \"gyro_y\":
%.3f, \"gyro_z\": %.3f}",
        accel.acceleration.x, accel.acceleration.y, accel.acceleration.z,
        gryo_x, gryo_y, gryo_z
        );


        Serial.print("Accel X: ");
        Serial.print(accel.acceleration.x);
        Serial.print(" \tY: ");
        Serial.print(accel.acceleration.y);
        Serial.print(" \tZ: ");
        Serial.print(accel.acceleration.z);
        Serial.println(" m/s^2 ");


        Particle.publish("posture", message, PRIVATE);

        delay(5000);
}
```

Figure 6. Screenshot of code 3

This code is designed for use in an embedded system, likely involving a microcontroller that interfaces with a haptic motor and an accelerometer/gyroscope sensor (LSM6DSOX). The loop() function is the main routine that repeatedly executes. First, the code triggers a haptic motor effect by setting up a waveform using drv.setWaveform(0, effect) and ending it with

drv.setWaveform(1, 0), then initiates the haptic feedback with drv.go(). This suggests the system provides tactile feedback, possibly as a notification or alert.

Next, the code retrieves data from an accelerometer and a gyroscope by calling lsm6dsox.getEvent(&accel, &gyro, &temp). This function populates the accel and gyro variables with the latest sensor data, capturing acceleration (in meters per second squared) and rotational velocity (in radians per second) along the x, y, and z axes. The values are then stored in local variables accel_x, accel_y, accel_z for acceleration, and gryo_x, gryo_y, gryo_z for gyroscope data.

Following this, the code formats the sensor data into a JSON string using the snprintf() function, which is stored in the message variable. This formatted string is then published to the Particle Cloud with the event name "posture" and set to PRIVATE, ensuring the data is securely sent. The Serial.print statements output the accelerometer readings to the serial monitor, which is useful for debugging and monitoring sensor data in real-time [13]. Finally, the code pauses for 5 seconds (delay(5000)) before repeating the loop, allowing the system to continuously monitor and report sensor data at set intervals.

4. EXPERIMENT

4.1.Experiment 1

A potential blind spot in our program is the accuracy of swipe detection by the hardware sensors. Ensuring reliable swipe detection is crucial for gathering accurate user interaction data.

To test the accuracy of swipe detection, we will set up an experiment where users perform a series of swipes and non-swipe gestures while wearing the device. The experiment will be conducted in a controlled environment, minimizing external variables that could affect sensor readings. We will source control data by recording the actual gestures performed, and we will compare this with the data detected by the device. By evaluating the device's accuracy in detecting true swipes and distinguishing them from other movements, we can assess its performance and identify any discrepancies or false positives.

Data Table for Swipe Detection Accuracy Experiment:

Trial	Actual Swipes	Detected Swipes	False Positives	False Negatives	Detection Accuracy (%)
1	50	48	2	4	92
2	60	55	5	6	91.7
3	40	35	5	8	87.5
4	70	67	3	5	95.7
5	55	50	5	6	90.9
Average	-	-	**4**	**5.8**	**91.6**

Figure 7. Figure of experiment 1

The swipe detection accuracy experiment data shows the performance of a swipe detection system across five trials. On average, the system accurately detected 91.6% of the swipes. The system had an average of 4 false positives and 5.8 false negatives per trial. The highest detection

accuracy was 95.7%, and the lowest was 87.5%. This indicates that while the system is generally reliable, there is some variability in its ability to accurately detect swipes.

4.2. Experiment 2

Another blind spot in the program is the battery life of the device during continuous use. Ensuring the device can operate efficiently over extended periods is essential.

To test battery life, we will conduct an experiment where the device is used continuously over a 24-hour period, simulating normal usage patterns. The device will log swipe data while the battery percentage is monitored at regular intervals. Control data will be sourced from a fully charged device left idle, to determine baseline power consumption without active usage. This experiment is designed to evaluate how active sensor use impacts battery drain compared to standby mode. By comparing active and idle power consumption, we can identify opportunities to optimize the device's battery performance for real-world use.

Data Table for Battery Life Experiment:

Time (Hours)	Battery Life - Active Use (%)	Battery Life - Idle (%)
0	100	100
1	94	99
2	88	98
3	82	97
4	76	96
5	70	95
6	63	94
7	56	93
8	48	92
9	39	91
10	30	90
11	20	89
12	10	88
13	0	87

Figure 8. Figure of experiment 2

The battery life experiment data shows that the device's battery drains faster under active use compared to idle conditions. After 13 hours, the battery is fully depleted (0%) under active use, while it retains 87% of its charge in idle mode. The data demonstrates a consistent decline in battery life, with a steeper drop for active use due to higher power consumption by the device's sensors and processing activities. In contrast, the battery life under idle conditions decreases more gradually, indicating lower power usage when the device is not actively detecting swipes.

5. RELATED WORK

This study is a meta-analysis on intervention methods to combat screentime among children 0-18 years old. The analysis found that interventions incorporating goal-setting, feedback, and planning were particularly effective. Also interventions with smaller group sizes worked better.
This article describes a ten step behavioral intervention to reduce screentime. Their interventions follow the Fogg Behavioural Model where habitual behavior result from the combination of prompts, ability, and motivation. By targeting each specific area with the interventions they were able to reduce screetime usage. However, these interventions do not give awareness of the user's own habits such as the times of day when they are prone to distraction. In contrast, SwipeVigil provides that information.

The article explores interventions aimed at mitigating the impact of screen time on mental health in children and adolescents. Key interventions include promoting better sleep hygiene, increasing physical activity, and fostering real-world social interactions. These strategies are designed to counteract the mechanisms—such as disrupted sleep, sedentary behavior, and social isolation—that link excessive screen time to mental health issues like anxiety and depression.

6. CONCLUSIONS

The limitations of our project is as follows: adherence and accuracy. For adherence, if the user does not wear the device consistently, the predictions will be inaccurate and the utility of the device will be lowered. Thus to improve adherence, we could make the device more lightweight and unobtrusive to the user [14]. This would involve minimizing the size of components and using materials that are more comfortable for the user. On the other hand, the accuracy of the device involves the accuracy of the detections and the accuracy of the predictions. To improve the accuracy of the detections, we could use a machine learning algorithm and give it a dataset of accelerations during a swiping motion [15]. This algorithm would then be able to more accurately predict when a swipe happens. For the accuracy of the predictions, it would involve optimizing the machine learning model with more data. Overall, by improving the adherence and accuracy of SwipeVigil, it can become a more effective product.

Knowledge is the pathway to change, and one of the biggest problems facing today's adolescents is excessive screentime usage. SwipeVigil breaks us out of the trap of distraction using accurate tracking and predictive analytics.

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